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Revealing Crisis Communication Dynamics in the Arab World on Platform X

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Abstract: The Arab world has witnessed various disasters, both natural and human-made, that have had profound impacts on communities and societies. Addressing and mitigating the impact of these disasters require effective disaster response strategies, community resilience initiatives, and international collaboration. Understanding the dynamics of social networks during such crises is crucial for developing proactive and informed disaster management approaches in the Arab world. This study explores the dynamics of social networks and influential figures on social media platform X during significant crises in the Arab world. Utilizing Social Network Analysis (SNA), the research compiles Arabic datasets, visualizes social networks, identifies information sources, and highlights influential figures. The findings of this work contribute to a deeper understanding of communication patterns during disasters, guiding evidence-based decision-making and optimizing resource allocation in disaster response efforts.

Keywords: Social Network Analysis, Influential Figures, Disaster Response, Disaster Management, Social Media.

I. INTRODUCTION

Over the past two decades, there has been a significant rise in natural disasters globally, causing significant human casualties, fatalities, and extensive property damage[1]. Notable instances include the Indonesia tsunami, Haiti earthquake, Sudanese drought, Iranian earthquakes, and European heat waves. The year 2023 witnessed numerous disasters, including wildfires in Greece, floods in Slovenia, a tropical cyclone in Brazil, and crises in the Middle East and Arab World. Particularly impactful were the devastating earthquake in Turkey and Syria, seismic activity in Morocco, and the effects of Hurricane Daniel in Libya. These events underscore the increasing challenges faced by cities worldwide in the wake of natural disasters.

Social Network Analysis (SNA) stands as a methodological and quantitative approach employed to scrutinize social structures and relationships among entities, typically depicted as nodes and ties within a network [2]. This analytical framework entails the systematic exploration of patterns of connections and interactions aiming to derive valuable insights into the intricate structure, dynamic evolution, and operational mechanisms of social systems [2]. Through the meticulous analysis of relationships and affiliations, SNA provides a means to unravel the complexities inherent in the fabric of social networks, offering researchers and practitioners a comprehensive tool to comprehend the underlying dynamics of interpersonal connections and their broader implications within societal frameworks.

In the realm of disasters, SNA is a methodology that delves into the examination of relationships, interactions, and the flow of information within social networks [3]. Its primary aim is to foster a deeper understanding and enhancement of disaster response and recovery efforts [3]. By comprehending how information disseminates through social networks, this approach contributes to refining communication strategies, thus increasing their efficacy.

Moreover, SNA serves as a valuable tool for identifying key actors or influential individuals within social networks during disasters. In essence, SNA in the context of disasters offers profound insights that can guide evidence-based decision-making, fortify community resilience, and facilitate the optimized allocation of resources for more effective disaster management.

The utilization of social media by the public during crisis events can yield an excess of information that holds significant value for crisis managers and officials. Consequently, SNA has been frequently employed to explore the interactions among users on social media platforms during crises [4]. For instance, an investigation into the network of retweets and replies among Twitter accounts during the 2017 Storm Cindy in the US uncovered key accounts that served as dominant sources of information. Notable findings from analyses conducted during events like Hurricane Irene, the England riots, and the 2011 Virginia earthquake revealed distinct user communities on Twitter [5]. These studies shed light on the dynamics of information exchange among interconnected actors, represented by user accounts, as crises unfold.

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Social media platforms like X can contribute to nearly instantaneous situational awareness among the public [4]. Moreover, disasters and X share a close relationship, for instance, outbreaks of epidemics often lead individuals to share their opinions and experiences on Twitter [6]. Research has delved into whether Twitter functions more as a social network or a news media outlet, with preliminary findings indicating that some aspects of Twitter differ from other social media platforms and that a substantial amount of user-generated content on Twitter is news-related [7]. X plays a significant role in contributing diverse categories of information to enhance situational awareness during hazards [8]. Recognizing this, there is a growing impetus to enhance our comprehension of X and its user and networks characteristics in the Arab world, aiming to contribute to more effective disaster response efforts in the region. This study makes several contributions, including:

- Compilation of three Arabic corpora from X, each focusing on a significant crisis that has affected the Arab world.
- Visualization of social networks pertaining to three disasters in the Arab world.
- Identification of the information sources utilized by X users in the Arab world during these disasters.
- Identification of the most influential figures among the disasters.

The subsequent sections of the Research are arranged as follows: the second section delves into the Literature Review, the third section outlines the Methodology, followed by the results in the fourth section. The fifth section engages in the Discussion, and finally, the Conclusion is presented in the last section.

II. LITERATURE REVIEW

A. Background

SNA is a typical example of an idea that can be used in many domains. With mathematical graph theory, it has become a multidisciplinary technique with applications in the information sciences, sociology, computer sciences, geography etc. SNA enables calculating measures and drawing graphs that illustrate the structure of a network. There are several measures to evaluate networks and determine their attributes. These measures collectively contribute to a comprehensive analysis of the network's structure, identifying key nodes, patterns, and properties. SNA's broad applicability makes it a powerful tool for understanding complex relationships and dynamics in diverse fields. Below are the most prevalent and significant.

- Degree Centrality: degree centrality corresponds to the number of actors with whom a particular actor is directly related [9]. In mathematical terms degree centrality, $d(i)$ of node i is defined as:

$$d(i) = \sum_{j} m_{ij}$$

  where m_{ij} =1 if there is a link between nodes i and j and m_{ij} = 0 if there is no such link.

- Betweenness Centrality: betweenness centrality is defined as the number of times a node requires a given node to reach another node. Also defined as the number of shortest paths that pass-through a given node [9]. As a mathematical expression the betweenness centrality of node i, denoted as $b(i)$ is obtained as:

$$b(i) = \sum_{j,k} \frac{g_{jik}}{g_{jk}}$$

  where g_{jk} is the number of shortest paths from node j to node k, and g_{jik} is the number of shortest paths from node j to node k passing through node i, $(j, k \neq i)$.

- Closeness Centrality: closeness centrality of a node is equal to the total distance of this node from all other nodes[9]. With closeness centrality, it is possible to know how closely actors are connected to the entire social network. As a mathematical formula closeness centrality, $C(i)$ of node i can be written as:

$$C(i) = \sum_{i} d_{ij}$$

  where d_{ij} is the number of links in a shortest path from node i to node j.

- Density: is an indicator of the general level of connectedness of the network [10]. Is defined as the number of links observed between a set of nodes, expressed as a proportion of the total number of ties possible for that set of nodes. Where ties are binary density scores vary between 1 (every possible tie is observed) and 0 (no ties).

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- Average Distance: In mathematics, the average distance between nodes in a graph is a measure that quantifies the typical separation or connectivity within the graph [11]. Specifically, it refers to the average shortest path length between all pairs of nodes in the graph. The average distance is calculated by finding the shortest path (minimum number of edges or links) between every pair of nodes in the graph and then computing the average of these shortest paths.
- Clustering Coefficient: The overall clustering coefficient for the entire graph is calculated as the average of the clustering coefficients for all individual nodes in the graph [11]. A higher overall clustering coefficient indicates a network where nodes are more likely to be part of local clusters, while a lower value suggests a more dispersed or decentralized structure.
- Diameter: The diameter of a graph is the longest shortest path between any two nodes in the graph. In other words, it is the maximum distance (number of edges) between any pair of nodes [11]. In practice, calculating the diameter involves finding the shortest paths lengths between all pairs of nodes and identifying the longest of these paths.
- Transitivity: Often referred to as the global clustering coefficient, is a measure of how interconnected nodes in a graph tend to be. It quantifies the likelihood that the neighbours of a node are also connected to each other[11]. In other terms, transitivity measures the extent to which nodes tend to form closed triangles in the graph. Higher transitivity values suggest a higher likelihood of clustering in the network, indicating a structure where neighbours of a node are more likely to be connected to each other.

B. The Role of Social Media in Disasters

The utilization of social media has experienced a significant surge in the past decade, particularly before, during, and after both human-induced and natural disasters, as highlighted in studies by Graham et al. and Reuter et al.[12, 13]. Emergency management agencies have embraced social media platforms as essential tools for various purposes such as documenting unfolding events, exchanging information with the public, raising awareness about disasters, facilitating donation management, and mobilizing volunteers, as outlined by Houston et al. [14]. During specific events like Hurricane Harvey, Twitter became a crucial channel for emergency organizations to disseminate imperative instructions in advance of the storm's landfall, as demonstrated by the findings of [15]. Below is a more research that has employed social media in disaster contexts.

[16] present a framework employing deep learning-based language models for sentiment analysis of tweets during the rise of COVID-19 cases in India. Another study aimed to improve disaster relief efficiency by mining and analyzing social media data, focusing on public attitudes towards disaster response and demands for targeted relief supplies during different disasters [17]. [18] investigated various natural disasters and their representation on Twitter through sentiment analysis. The study provided a social network perspective on the representation and sentiments related to different natural disasters on Twitter. According to [19] the dataset of study was sourced from Twitter and aimed to employs social media text messages to create a damage map following the South Napa earthquake. Also, another study introduces a novel method for integrating information from diverse networks on social media to enhance the predictability of evacuees' returning behavior after severe disasters [20].

C. Application of SNA in Disasters

The literature on the application of SNA in disaster management demonstrates its significance in enhancing our understanding of social structures, communication patterns, and resource flows. The utilization of SNA has proven to be instrumental in improving the efficiency and effectiveness of disaster response and recovery efforts. Several studies have contributed valuable insights into various aspects of disaster management using SNA.

Sadri et al. (2017) conducted a study during Hurricane Sandy, analyzing Twitter data to understand information spreading activities on social media. The research emphasized the importance of centrality, eccentricity, and degree in user activity during information dissemination [21]. Marx et al. (2020) investigated the communication strategies of media organizations during Hurricane Harvey. The study highlighted the crucial role of local media outlets in disaster communication and underscored the significance of their sense-giving function during crises [22]. Kim and Hastak (2018) applied SNA to emergency social network data after a disaster, providing insights into the structure of social networks during emergencies and the roles played by different entities [23]. Dong et al. (2018) focused on information diffusion during natural disasters, considering individual characteristics, social relationships, and interaction network topology. The study shed light on factors influencing information diffusion during disasters, emphasizing the role of user characteristics and network structure [24] . Active players and their effectiveness were analyzed in disseminating critical information aimed to understand online communities during the Australian floods. SNA revealed that citizens' direct participation in retweeting significantly influenced the speed and reach of government Twitter warnings [25] .

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During Hurricane Harvey, Rajput et al. (2020) conducted a temporal network analysis of inter-organizational communications on social media. The study focused on the Arabic-speaking community during the COVID-19 pandemic, utilizing Twitter data [26]. Twitter communication data related to the 2016 Southern Louisiana flood recovery process was analyzed. The study indicated a decreasing communication volume during the recovery phase, a lack of local voices in long-term recovery communication, and the persistence of negative sentiments throughout the recovery period [27].

Most of this research focused on regions where Arabic is not the primary language. Hence, the knowledge gap is specifically centered on the lack of extensive Arabic corpora designed to address significant crises affecting the region. Additionally, there is a critical need to visually analyze and understand the social networks associated with these disasters, identify the primary information sources accessed by users on platform X during crises, and recognize the influential figures shaping the discourse in Arab world. The absence of these comprehensive insights poses a barrier to the formulation of effective crisis management and response strategies, emphasizing the vital importance of this study in addressing and closing these crucial knowledge gaps.

III. METHODOLOGY

The methodology involves several key processes, data acquisition from X, data pre-processing, application of SNA techniques, network visualization, identification of network characteristics, identification of influencers and information sources. The flow of the research methodology is depicted in Figure 1.

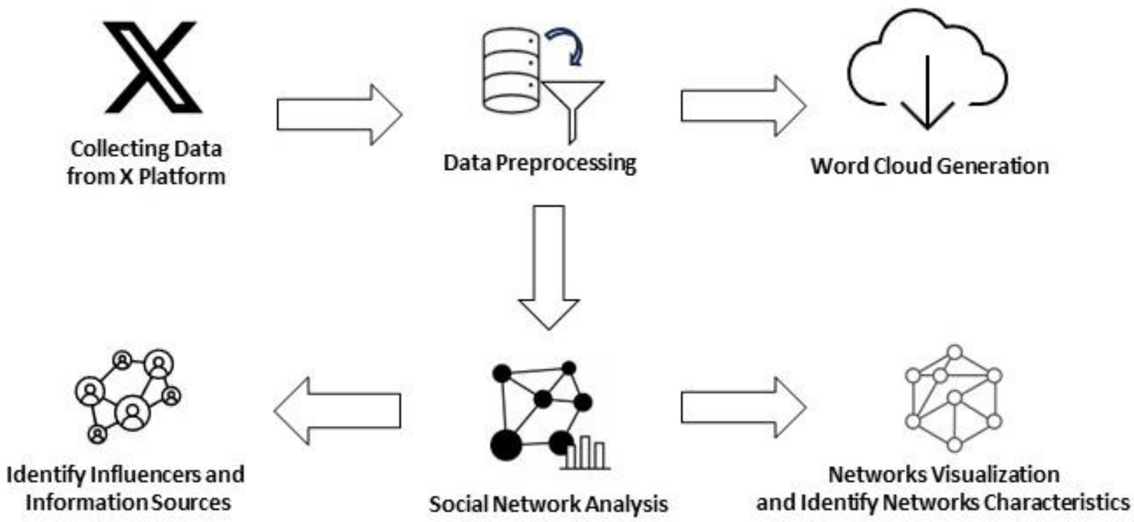

Fig 1: Flow of Research Methodology

A. Data collection

For collecting data of Turkey and Syria earthquake, the study utilized Netlytic a tool for collecting public streams of information [28]. The dataset encompasses posts, post information (e.g., repost, likes), and user details (e.g., geolocation, follower count). Due to X discontinuing its free API, Netlytic can no longer directly collect data from X. Therefore, for the Morocco earthquake and Hurricane Daniel, Communalytic.org was employed with an X API key [29]. Communalytic serves as a computational social science research tool designed for analyzing online communities and discourse, capable of collecting, analyzing, and visualizing publicly available data from various platforms, including X [29].

Concerning the earthquake in Turkey and Syria, the study gathered a dataset comprising 100,000 tweets, spanning from February 6 to February 12, 2023, capturing public reactions and discussions during that period. However, with regards to the Morocco earthquake and Hurricane Daniel, limitations imposed by the Communalytic.org and the Basic X API dictate that only 10,000 tweets can be retrieved per month. Consequently, we collected approximately 10,000 tweets for both events, with a notable concentration around September 12, 2023, for the Moroccan earthquake, and September 15, 2023, for Hurricane Daniel, in accordance with platform policies.

Table 1 provided below illustrates a sample of the posts that were retrieved concerning the three disasters. Finally, the keywords employed for data extraction are illustrated in Table 2.

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TABLE I SAMPLE OF DATA COLLECTED FOR THE THREE DISASTERS

	ARABIC POST	ENGLISH TRANSLATION
SYRIA AND TURKIE EARTHQUAKE	الصحة العالمية: 26 مليون شخص تأثروا بـ #الزلزال #زلزال_تركيا_وسوريا في #سوريا و #تركيا https://t.co/Zecn0L9tG5	World Health: 26 million people were affected by the #earthquake in #Syria and #Turkey #Turkey_and_Syria_earthquake
MOROCCO EARTHQUAKE	RT @milonario37: " ما عدت قادرة على متابعة التلفاز، ليس لدي ما اساعد به سوى خاتم الذهب هذا" 🀆❤️ دموع شباب بعد كلمات مؤثرة من ام مغربية اصيل…	RT @milonario37: "I can no longer watch TV, I have nothing to help with except this gold ring" 🀆❤️ Tears of youth after touching words from an authentic Moroccan mother...
HURRICANE DANIAL	RT @Sanaa645321412: تعازينا الحارة للشعب الليبيي الشقيق الله يتقبل شهداءكم ويعافي مريضكم ويصبركم على مصابكم الله يرحم موتاكم ويشفي جرحاكم…	RT @Sanaa645321412: Our deepest condolences to the brotherly Libyan people May God accept your martyrs, heal your sick, and give you patience in your affliction May God have mercy on your dead and heal your wounds...

TABLE 2 ARABIC KEYWORD/ HASHTAG USED TO GATHERING DATA

	ARABIC KEYWORD/HASHTAG	ENGLISH TRANSLATION
SYRIA AND TURKIE EARTHQUAKE	#زلزال_تركيا_وسوريا	#Turkey_and_Syria_earthquake
MOROCCO EARTHQUAKE	زلزال المغرب	Morrocco Earthquake
HURRICANE DANIAL	#اعصار_دانيال	#Hurricane _Danial

B. Data Pre-processing

Following the retrieval of posts from X, the subsequent stage involves data pre-processing. This stage includes preparing, processing, cleaning, and filtering the data. The pre-process phase included the following procedures:

- **Removal of Punctuation Marks and Emoji:** Punctuation marks, such as "!.?:" and emoji were systematically removed during the cleaning process, as they did not contribute meaningful information for analysis.
- **Elimination of URLs:** The removal of URLs was imperative, considering that users often incorporated links in their posts that held no relevance to the tweet analysis.
- **Exclusion of Usernames:** Although usernames are intrinsic to individual posts, they were considered non-contributory to the analytical process and were therefore eliminated.
- **Handling Hashtags:** Hashtags, denoted by the "#" symbol, were systematically removed from the posts to ensure a focused and refined dataset.
- **Filtering Stop-Words:** Common stop-words like "هذا" ,"الى", "في," etc., were eliminated from the dataset to enhance the quality of the data for more accurate analysis.

C. Social Network Analysis

This phase focuses on conducting a comprehensive quantitative network analysis, aiming to illustrate the principal properties of the three disaster networks. To answer the research question, Social Network Analysis (SNA) was utilized and perform three types of analyses: (1) computation of metrics offering both local (actor-level) and global (network-level) insights, (2) graphical visualization of the network, and (3) centrality measures. One fundamental aspect of social network analysis involves identifying significant and influential nodes within the network. Centrality measures serve as widely utilized indices in the realm of network data, typically indicating the importance of a node based on factors such as its status, visibility, structural power, or prestige [30]. In this study, we utilized prominent centrality measures, including degree, closeness, and betweenness, to assess the significance and influence of nodes in the social network. To address the escalating demand for social network data mining and visualization technology, various software and tools

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have been developed. The research employed Python3 for social network analysis, generation of word cloud [31]. Additionally, Gephi was utilized for network visualization purposes [32]. Gephi provides users with multiple layout options, and ForceAtlas2 is among the available choices. The research used ForceAtlas2 layout. This layout operates as a force-directed layout algorithm, simulating a physical system to arrange nodes within a network. Nodes behave like charged particles, exerting repulsive forces on each other, while edges act like springs, pulling connected nodes together. The interplay of these forces results in a dynamic movement that gradually converges to a balanced state. The ultimate layout is intended to enhance the interpretability of the network data [33].

D. Word Cloud Generation

Subsequently, word clouds were generated for the disaster networks. The term "word cloud" pertains to the visualization depicting the frequency of words, where the size of each word in the cloud corresponds to its prevalence in the text. Word clouds are a widely adopted method for visualizing textual content and used in all relevant across various domains. They prove effective in examining Twitter content, facilitating the assessment of public opinions on specific topics.

IV. RESULT

In the realm of social network analysis, graph theory concepts are employed to gain insights into and assess social phenomena. To provide an initial visual representation of the overall graphs, Figures 2, 3, and 4 illustrate the social networks related to the three different disasters. The graphs are undirected, and the layout was generated using the ForceAtlas2 algorithm. This network layout encompasses both the circle nodes (representing users) and the interactions (edges) between them. We observe varying levels of user interactions within the depicted figures. In Figure 2 and Figure 3, there are notable high levels of interactions for users, as evident in the lower right portion of Figure 2 and Figure 3. Similarly, in Figure 4, the middle section shows a considerable amount of interaction. On the other hand, some users exhibit low interaction levels, particularly those positioned around the periphery of Figure 4.Following the earthquakes in Turkey and Syria, a substantial 78% of posts were reposted content. In the case of the Morocco earthquake, 66% of the total posts were reposts, and for Hurricane Daniel, 72% of posts were also reposted. Our analysis of these networks revealed that the diameter was 15 hops for the Syria Earthquake network and 17 hops for the Morocco Earthquake and 24 hops for Hurricane Daniel networks. According to Average Distance, the distances are relatively close for all three events, with Hurricane Daniel network having the highest average distance at 6.8773, implying a slightly more disconnected network. In terms of network density, all three networks demonstrate low levels of density. For more detailed information. Table 3 provides a summary of various metrics related to these three distinct disaster events. These metrics offer valuable insights into the X activity surrounding these events.

TABLE 3 OVERAL GRAPH METRICS

METRICS	SYRIA AND TURKEY EARTHQUAKE	MOROCCO EARTHQUAKE	HURRICANE DANIEL
# POST	100000	12162	11839
REPOST	78%	66%	72%
# NODE	44429	5269	6543
# EDGES	61917	6840	7318
# CONNECTED COMPONENT	934	479	451
# NODE IN LARGEST COMPONENT	41559	3239	4544
# EDGES IN LARGEST COMPONENT	59796	4997	5877
AVERAGE DISTANCE	5.0244	5.6648	6.8773
DENSITY	0.00006	0.0009	0.0005
DIAMETER	15	17	24
TRANSITIVITY	0.0007	0	0
CLUSTERING COEFFICIENT	0.0098	0	0

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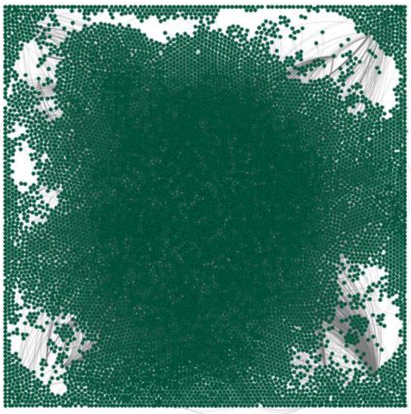

Fig 2: The initial representation of the overarching social network structure of Syria and Turkey Earthquake

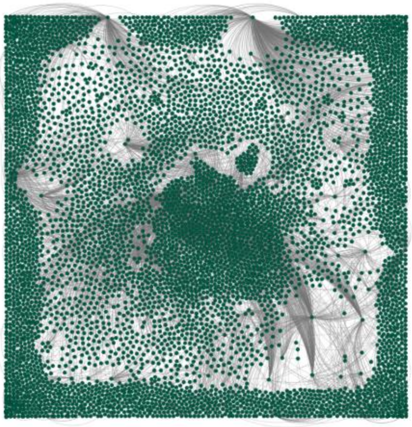

Fig 3: The initial representation of the overarching social network structure of Hurricane Danial

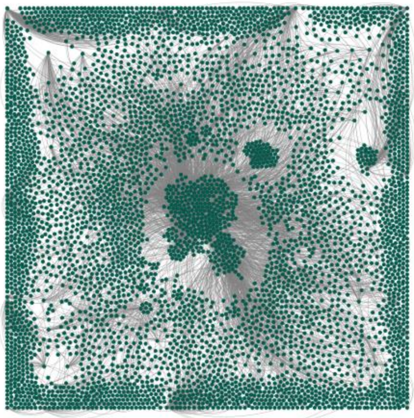

Fig 4: The initial representation of the overarching social network structure of Morocco Earthquake

According to graph theory, centrality measures may reveal characteristics and social ties of certain network participants [34]. In our study, we found that the account with the highest betweenness centrality is @AhmedHAlKhalili (Official account of Mufti Oman) with a value of 0.1304 in the Syria Earthquake network, @hespress (Moroccan electronic newspaper account) with a value of 0.2207 in the Morocco Earthquake network, and @Arab_Storms (Unofficial account dedicated for weather news)with a value of 0.4361 in the Hurricane Daniel network. The top-ranked accounts across the three disaster networks in degree centrality were @AhmedHAlKhalili with a score of 0.0618 in the Syria Earthquake network, @hespress with a score of 0.0649 in the Morocco Earthquake network, and @UAEAid (Formal account associated with the United Arab Emirates promoting peace and prosperity)with a score of 0.1140 in the Hurricane Daniel network.

Closeness Centrality is a metric that gauges the degree of central influence a user or entity holds concerning the efficient flow and sharing of information within a network. Notably, the most prominent accounts in this regard were @OrientNews (Official account of Syrian TV) with a score of 0.3002 in the Syria Earthquake network, @hespress with a score of 0.2801 in the Morocco Earthquake network, and @Arab_Storms with a score of 0.2458 in the Hurricane Daniel network. The information presented in Table 4 illustrates the top 10 influential accounts, determined through centrality metrics (Betweenness BC, Closeness CC, Degree DC), within the networks related to the three occurrences: the Syria Earthquake, Morocco Earthquake, and Hurricane Daniel.

TABLE 4 TOP 10 INFLUENCERS BASED ON CENTRALITY MEASURES

Syria Earthquake		***Morocco Earthquake***		***Hurricane Danial***	
Account	**BC**	**Account**	**BC**	**Account**	**BC**
@AhmedHAlKhalili	0.1304	@**hespress**	0.2207	@Arab_Storms	0.4361
@ramiaalibrahim	0.1253	@NabilAlawadhy	0.1381	@**skynewsarabia**	0.2583
@7usaini7	0.1047	@milonario37	0.1241	@alsyaaq	0.2322
@aamshaya	0.0871	@5_ersito	0.1044	@Abdullaslamry32	0.2301
@**OrientNews**	0.0868	@derradjihafid	0.0963	@UAEAid	0.2146
@Omar_Madaniah	0.0742	@vivalalgerie7	0.0803	@Pel33508446	0.1857
@Nazli_Tu	0.0706	@BnshKhaled	0.0748	@DGPC_CNI	0.1557
@Arab_Storms	0.0613	@HMeghribi	0.0725	@alsayg	0.1338
@**aa_arabic**	0.0466	@ahafsidz	0.0651	@4Hmod330	0.1261
@f_alabdulkarim	0.0450	@bsalsharari	0.0618	@alaa1984az	0.1200
Account	**DC**	**Account**	**DC**	**Account**	**DC**
@AhmedHAlKhalili	0.0618	@**hespress**	0.0649	@UAEAid	0.1140
@ramiaalibrahim	0.0484	@5_ersito	0.0568	@4Hmod330	0.0623
@7usaini7	0.0452	@milonario37	0.0522	@DGPC_CNI	0.0530
@aamshaya	0.0353	@HMeghribi	0.0432	@Arab_Storms	0.0486
@Nazli_Tu	0.0327	@Simo__Ben	0.0392	@rmdanjm13396441	0.0469
@**OrientNews**	0.0283	@derradjihafid	0.0343	@alsayg	0.0434

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@Omar_Madaniah	0.0267	@bocchus_moro	0.0327	@knoz_services	0.0317
@Arab_Storms	0.0221	@NabilAlawadhy	0.0321	@ALMISNID	0.0315
@f_alabdulkarim	0.0183	@vivalalgerie7	0.0315	@**skynewsarabia**	0.0299
@drassagheer	0.0168	@ahafsidz	0.0293	@rahma_ali17	0.0291
Account	**CC**	**Account**	**CC**	**Account**	**CC**
@**OrientNews**	0.3002	@**hespress**	0.2801	@Arab_Storms	0.2458
@Omar_Madaniah	0.2982	@5_ersito	0.2670	@WahId91811199	0.2299
@Nazli_Tu	0.2979	@hananemaghribya	0.2662	@ABDULLAMULA194	0.2255
@**aa_arabic**	0.2974	@mustaphbaroudi	0.2606	@DrAyedAljuraid	0.2250
@AhmedHAlKhalili	0.2950	@AlhuraAlsa20415	0.2598	@**skynewsarabia**	0.2229
@Arab_Storms	0.2945	@bocchus_moro	0.2588	@alsayg	0.2219
@7usaini7	0.2920	@HMeghribi	0.2575	@twitt_fh	0.2194
@ramiaalibrahim	0.2911	@mohammedtaib8	0.2575	@Michael_M_Rezq	0.2173
@EssraTurke	0.2878	@mohsinelatif	0.2567	@iamYvonneBerry	0.2155
@bofaisl12	0.2857	@NabilAlawadhy	0.2530	@hasan5750000	0.2145

As demonstrated in the illustrations in Figure 5,6,7, the most frequently occurring keywords in the Hurricane Danial network were "Food aid" (المساعدات الغذائية), "search and rescue" (البحث الإنقاذ), and "airlift" (الجسر الجوي). Similarly, in the Morocco earthquake network, the most common terms were "Morocco earthquake" (زلزال المغرب) and "Moroccan people" (الشعب المغربي).

Meanwhile, in the Syria and Turkey earthquake network, prevalent phrases included "There is no power except in God" (قوة الا بالله), "Devastating death" (الموت المدمر). Furthermore, some unrelated words were also present in the data. These included some words about the prayer.

Fig 5: Word Cloud of Morocco Earthquake

Fig 4: Word Cloud of Hurricane Danial

Fig 7: Word Cloud of Syria and Turkey Earthquake

V. DISCUSSION

A. Study Findings

The findings reveal distinctive characteristics within the Syria Earthquake network. This network exhibits closely connected users, each within 15 steps of other users, given its 44,429 nodes. Despite the close connectivity, the average shortest path is 5, suggesting that a considerable number of nodes can be reached within less than 15 hops. However, the network's density is nearly zero (0.00006), and the clustering coefficient is 0.0098 , indicating a scarcity of connections relative to potential connections. This discrepancy is evident in the clustering coefficient, signifying a lack of interconnected neighbors, i.e., connected users do not share a mutual friend.

Unlike the other two networks, we observed that the two networks with the smallest number of nodes exhibited greater separation. In the Morocco earthquake network, the diameter was 17, and in Hurricane Daniel, it was 24, both considered substantial in relation to the respective node counts of 5,269 and 6,543. The average shortest distances were 5 and 6, indicating a relatively greater degree of separation. Additionally, the two networks displayed higher levels of separation in terms of density. Subgroup presence within the networks is limited across all cases.

The top 10 influencers in the three networks are individuals who cover a range of professions, including religious leadership, broadcasting, academia, media, writing, and social media influencing. However, in Networks of the Moroccan earthquake and Hurricane Danial there exist individuals who did not have many followers or friends.

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No doubt that the influence can vary and be context-dependent, and individuals may contribute to online discussions or communities in ways that might not be immediately apparent. Social media dynamics are fluid, and the impact of accounts can change over time based on their content, engagement, and evolving online trends.

Our investigation unveiled the primary information sources to which Twitter users frequently turned during the Syrian earthquake. Notably, @OrientNews and @aa_arabic emerged as the most referenced sources, securing positions among the top ten influencers based on centrality measurements. On the other hand, in the Morocco earthquake, only one information source account, @hespress, made it to the top ten influencers. In the context of Hurricane Daniel, two information source accounts stood out among the top ten influencers: @skynewsarabia and @DGPC_CNI. This indicates that the official information source Twitter accounts mentioned earlier were strategically positioned in the network, exercising control and influence over the dissemination of information during the disasters. It signifies that users place trust in the information disseminated by these accounts, considering them as primary sources of information. Additionally, these accounts possess the capacity to efficiently and rapidly propagate information compared to other official sources.

The number of influential accounts considered as official sources of information or official accounts such as government officials, emergency Agencies, institutions and news figures is small in networks of Moroccan earthquake and Hurricane Danial. This indicates that users tend to share messages published by an unreliable source of information, which will lead to the spread of misinformation. In contrast, noteworthy patterns emerged across three distinct studies [23, 24, 30]. In the first study, five official organization accounts ranked among the top ten influencers, whereas the second study identified six official information sources in a similar position. Interestingly, the third study highlighted that all users whose tweets consistently garnered widespread reposting were affiliated to news/charity organizations or entertainers. Similarly, in network of Turkey and Syria earthquake. This represents a justifiable rate for a single network.

The research confronted limitations in data collection resulting from modifications in X's policy. Specifically, the policy changes implemented by X, whether in terms of data accessibility or API restrictions, created impediments to the smooth and comprehensive acquisition of data crucial for the study. This has affected the frequency and volume of data that researchers were able to collect within a given timeframe. These alterations influenced the scope and depth of the data available, potentially impacting the research's ability to find robust conclusions or insights.

B. Study Recommendations

Based in view of the study's insights, it is recommended that official government agencies such as disaster monitoring organizations and emergency management agencies, and news entities actively participate in communicating with the public through social media platforms during instances of disasters. This proactive engagement is essential to facilitate the prompt and accurate dissemination of trustworthy information, thereby augmenting their capability to assume a leadership role in communication endeavors and effectively mitigate the propagation of misinformation.

Leveraging social media channels enhances the expeditious distribution of information, ensuring its reach to a diverse and extensive audience. This strategic approach holds particular significance for efficiently reaching individuals in need of assistance both during and in the aftermath of disasters. Moreover, establishing a partnership with social media platforms like X would enhance the credibility of data collection, facilitate real-time data monitoring, and streamline the overall SNA process during emergencies.

VI. CONCLUSION

This study has provided a comprehensive exploration of the intersection between SNA, disasters, and social media to fill existing knowledge gaps by delivering a comprehensive understanding of crisis-related dynamics in the Arab world, specifically within the realm of social media. The increasing frequency and impact of natural disasters globally, as exemplified by recent events, confirms the necessity for effective crisis management strategies. Social Network Analysis stands out as a robust methodology, offering valuable insights into the intricate social structures and relationships that play a pivotal role during disasters.

The application of SNA in disaster contexts has been demonstrated to enhance our understanding of communication patterns, identify key actors, and facilitate optimized resource allocation. By deepening our understanding of the dynamics of social networks during crises, especially in the context of social media platform X, this research seeks to contribute to the improvement of disaster response efforts in the Arab world.

Considering the study's findings, it is recommended that disaster monitoring organizations and news entities actively engage in communication through social media platforms during crises.

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This involvement is crucial for the accurate dissemination of reliable information, empowering these entities to take a leading role in communication efforts and effectively combating the spread of misinformation. For future work, a critical focus should be placed on studying communities in context of disasters, utilizing community detection methods. Such an approach plays a pivotal role in identifying affected groups or distinct communities, thereby highlighting specific populations or regions that may experience disproportionate effects.

Concurrently, there is a compelling need to delve into the analysis of sentiment on geographical maps within disaster contexts. This analytical exploration facilitates decision-makers in acquiring spatial insights into the emotional well-being of affected communities. The knowledge derived from such analyses is useful in formulating disaster response strategies that are not only targeted but also imbued with empathy and compassion.

REFERENCES

[1]. Z. Wang and X. Ye, '"Social media analytics for natural disaster management," *Int.J.Geogr.Inf.Sci.*, vol. 32, no. 1, pp. 49-72.
[2]. Ö Bodin and B.I. Crona, '"The role of social networks in natural resource governance: What relational patterns make a difference?" *Global Environ.Change*, vol. 19, no. 3, pp. 366-374.
[3]. B.C. Benedict, S. Lee, C.M. Jarvis, L.K. Siebeneck and R. Wolfe, '"Utilising qualitative data for social network analysis in disaster research: opportunities, challenges, and an illustration," *Disasters*.
[4]. A. Romascanu, H. Ker, R. Sieber, S. Greenidge, S. Lumley, D. Bush, S. Morgan, R. Zhao and M. Brunila, '"Using deep learning and social network analysis to understand and manage extreme flooding," *J.Contingencies Crisis Manage.*, vol. 28, no. 3, pp. 251-261.
[5]. A. Gupta, A. Joshi and P. Kumaraguru, '"Identifying and characterizing user communities on twitter during crisis events,", pp. 23-26.
[6]. J. Lee Boaz, M. Ybañez, M.M. De Leon and M.R.E. Estuar, '"Understanding the behavior of Filipino Twitter users during disaster," *GSTF Journal on Computing (JoC)*, vol. 3, pp. 1-6.
[7]. H. Kwak, C. Lee, H. Park and S. Moon, '"What is Twitter, a social network or a news media?", pp. 591-600.
[8]. S. Vieweg, A.L. Hughes, K. Starbird and L. Palen, '"Microblogging during two natural hazards events: what twitter may contribute to situational awareness,", pp. 1079-1088.
[9]. L.C. Freeman, '"Centrality in social networks: Conceptual clarification," *Social network: critical concepts in sociology.Londres: Routledge*, vol. 1, pp. 238-263.
[10]. E. Otte and R. Rousseau, '"Social network analysis: a powerful strategy, also for the information sciences," *J.Inf.Sci.*, vol. 28, no. 6, pp. 441-453.
[11]. S. Tabassum, F.S. Pereira, S. Fernandes and J. Gama, '"Social network analysis: An overview," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 8, no. 5, pp. e1256.
[12]. M.W. Graham, E.J. Avery and S. Park, '"The role of social media in local government crisis communications," *Public Relations Review*, vol. 41, no. 3, pp. 386-394.
[13]. C. Reuter, A.L. Hughes and M. Kaufhold, '"Social media in crisis management: An evaluation and analysis of crisis informatics research," *International Journal of Human–Computer Interaction*, vol. 34, no. 4, pp. 280-294.
[14]. J.B. Houston, J. Hawthorne, M.F. Perreault, E.H. Park, M. Goldstein Hode, M.R. Halliwell, S.E. Turner McGowen, R. Davis, S. Vaid and J.A. McElderry, '"Social media and disasters: a functional framework for social media use in disaster planning, response, and research," *Disasters*, vol. 39, no. 1, pp. 1-22.
[15]. W. Liu, C. Lai and W.W. Xu, '"Tweeting about emergency: A semantic network analysis of government organizations' social media messaging during hurricane Harvey," *Public relations review*, vol. 44, no. 5, pp. 807-819.
[16]. R. Chandra and A. Krishna, '"COVID-19 sentiment analysis via deep learning during the rise of novel cases," *PloS one*, vol. 16, no. 8, pp. e0255615.
[17]. Z.S. Dong, L. Meng, L. Christenson and L. Fulton, '"Social media information sharing for natural disaster response," *Nat.Hazards*, vol. 107, pp. 2077-2104.
[18]. K. Aziz, D. Zaidouni and M. Bellafkih, '"Social network analytics: natural disaster analysis through twitter,", pp. 1-7.
[19]. S. Ahadzadeh and M.R. Malek, '"Earthquake damage assessment based on user generated data in social networks," *Sustainability*, vol. 13, no. 9, pp. 4814.
[20]. T. Yabe and S.V. Ukkusuri, '"Integrating information from heterogeneous networks on social media to predict post-disaster returning behavior," *Journal of Computational Science*, vol. 32, pp. 12-20.
[21]. A.M. Sadri, S. Hasan, S.V. Ukkusuri and M. Cebrian, '"Understanding information spreading in social media during Hurricane Sandy: User activity and network properties," *arXiv preprint arXiv:1706.03019*.
[22]. J. Marx, M. Mirbabaie and C. Ehnis, '"Sense-giving strategies of media organisations in social media disaster communication: Findings from Hurricane Harvey," *arXiv preprint arXiv:2004.08567*.

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DOI: 10.17148/IJARCCE.2024.13215

[23]. J. Kim and M. Hastak, '"Social network analysis: Characteristics of online social networks after a disaster," *Int.J.Inf.Manage.*, vol. 38, no. 1, pp. 86-96.

[24]. R. Dong, L. Li, Q. Zhang and G. Cai, '"Information diffusion on social media during natural disasters," *IEEE transactions on computational social systems*, vol. 5, no. 1, pp. 265-276.

[25]. F. Cheong and C. Cheong, '"Social media data mining: A social network analysis of tweets during the 2010-2011 Australian floods,".

[26]. A.A. Rajput, Q. Li, C. Zhang and A. Mostafavi, '"Temporal network analysis of inter-organizational communications on social media during disasters: A study of Hurricane Harvey in Houston," *International journal of disaster risk reduction*, vol. 46, pp. 101622.

[27]. J. Yeo, C.C. Knox and Q. Hu, '"Disaster recovery communication in the digital era: Social media and the 2016 southern Louisiana flood," *Risk analysis*, vol. 42, no. 8, pp. 1670-1685.

[28]. A. Gruzd, P. Mai and A. Kampen, '"A how-to for using Netlytic to collect and analyze social media data: A case study of the use of Twitter during the 2014 Euromaidan Revolution in Ukraine," *The SAGE handbook of social media research methods*, pp. 513-529.

[29]. A. Gruzd and P. Mai, '"Communalytic A Research Tool For Studying Online Communities and Online Discourse.".

[30]. A.A. Al-Shargabi and A. Selmi, '"Social network analysis and visualization of Arabic tweets during the COVID-19 pandemic," *Ieee Access*, vol. 9, pp. 90616-90630.

[31]. M. Summerfield, '"Programming in Python 3: a complete introduction to the Python language,", 2010.

[32]. M. Bastian, S. Heymann and M. Jacomy, '"Gephi: an open source software for exploring and manipulating networks,", vol. 3, no. 1, pp. 361-362.

[33]. M. Jacomy, T. Venturini, S. Heymann and M. Bastian, '"ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software," *PloS one*, vol. 9, no. 6, pp. e98679.

[34]. S. Wasserman and K. Faust, '"Social network analysis: Methods and applications,".

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